Comparative Analysis of Time Series Models for Energy Consumption Forecasting in Brazilian Regions

Abstract

Accurate energy consumption forecasting is critical for optimizing resource allocation, reducing operational costs, and improving infrastructure planning. This study evaluates five forecasting models—ARIMA, SARIMA, Prophet, LSTM, and GRU—on monthly energy consumption data from Brazil (2004–2021). The GRU model achieved the best performance with an RMSE of 307,000 MWh and R^2 of 0.989, followed closely by the LSTM model (RMSE: 353,000 MWh, R^2: 0.984). Traditional models (ARIMA, SARIMA, Prophet) underperformed, with Prophet yielding a negative R^2 (-0.53). Results highlight the superiority of deep learning models in capturing complex temporal patterns, emphasizing their utility for energy management in geographically diverse regions like Brazil. The study provides actionable insights for utilities, policymakers, and researchers to improve forecasting accuracy and energy planning.

---

1. Introduction

Brazil's energy consumption varies significantly across its federative units due to factors such as population density, economic activity, industrial growth, climate variations, and seasonal demand fluctuations. Accurate forecasting enables utilities to mitigate inefficiencies, plan infrastructure investments, and reduce waste. Traditional statistical models such as ARIMA and SARIMA have been widely used for time series forecasting due to their interpretability and effectiveness in handling stationary data. However, recent advancements in deep learning, particularly recurrent neural networks like LSTM and GRU, offer potential improvements in capturing non-linear dependencies and long-term temporal patterns.

This study aims to:

- Compare the performance of statistical and neural network models for energy forecasting.

- Identify regional consumption trends and inefficiencies.

- Provide actionable insights for optimizing energy distribution and infrastructure planning.

---

2. Methodology

2.1 Dataset

- *Source*: Monthly energy consumption data from Brazil's National Electric Energy Agency (2004–2021).

- *Features*:

  - Date (timestamp format for time series modeling)

  - Federative unit (UF)

  - Consumption (MWh)

  - Consumer type (residential, industrial, commercial, etc.)

  - Temperature and humidity (extracted from meteorological datasets for feature enrichment)

- *Preprocessing*:

  - Aggregated daily consumption to monthly values to align with forecasting objectives.

  - Imputed missing values using group-wise means and linear interpolation.

  - Applied MinMax scaling for neural networks to normalize input values and improve training stability.

  - Performed data augmentation by incorporating rolling averages and differencing to enhance pattern recognition.

2.2 Forecasting Models

- *ARIMA/SARIMA*: Auto-ARIMA selected optimal parameters (SARIMA(0,1,0)(1,0,0)[12]) using AIC minimization.

- *Prophet*: Additive model with default seasonality settings and Fourier transformations for capturing periodic patterns.

- *LSTM/GRU*: Three-layer architectures with dropout regularization, hyperparameter tuning using grid search, and batch normalization for stability.

2.3 Evaluation Metrics

- *Mean Absolute Error (MAE)*: Measures the average magnitude of errors.

- *Root Mean Squared Error (RMSE)*: Emphasizes large errors, making it a key metric for energy forecasting.

- *R^2 (Coefficient of Determination)*: Indicates the proportion of variance explained by the model.

- *Mean Absolute Percentage Error (MAPE)*: Used for assessing percentage-based forecasting accuracy across regions.

---

3. Results

3.1 Model Performance

Model	MAE (MWh)	RMSE (MWh)	R^2
GRU	255,000	307,000	0.989
LSTM	278,000	353,000	0.984
Prophet	3,308,000	3,576,000	-0.53
ARIMA	3,781,000	4,930,000	-0.20
SARIMA	3,761,000	5,211,000	-0.34

3.2 Key Findings

- *Deep Learning Superiority*: GRU and LSTM outperformed traditional models, with GRU achieving the lowest RMSE and highest R^2.
- *Prophet Limitations*: Prophet struggled with non-linear patterns and exhibited poor generalization to high-variance energy consumption data.
- *Regional Trends*: Northern states (e.g., RR, TO) exhibited the highest compound annual growth rate (CAGR) of 6.4–6.5%, signaling rapid urbanization and economic expansion.
- *Industrial Dominance*: Industrial consumption accounted for 45% of total energy usage, highlighting the need for sector-specific infrastructure investments.
- *Seasonal Impact*: Winter months exhibited lower consumption in residential sectors, while summer months had peak demand due to air conditioning loads.

---

4. Discussion

4.1 Model Interpretations

- *GRU/LSTM*: These models excel in modeling sequential data due to their ability to learn long-term dependencies. GRU, with fewer parameters, performed slightly better, indicating reduced computational complexity and faster convergence.

- *Prophet*: While effective in datasets with well-defined seasonality, Prophet struggled with erratic energy demand variations and external factors like economic downturns.

- *ARIMA/SARIMA*: These models, constrained by linear assumptions, failed to capture complex energy consumption dynamics, leading to suboptimal performance.

4.2 Practical Implications

- *Infrastructure Planning*: High-growth regions (e.g., RR, TO) require targeted investments in power grids, renewable energy integration, and demand-side management strategies.

- *Efficiency Gaps*: The discrepancy in per-capita consumption (e.g., industrial energy use being 12% higher than residential) suggests the need for energy efficiency policies and demand-response mechanisms.

- *Renewable Energy Integration*: Given the volatile energy demand patterns, accurate forecasting could support the integration of wind and solar power sources, optimizing grid stability.

---

5. Conclusion

GRU and LSTM models demonstrated superior accuracy in forecasting Brazil's energy consumption, enabling utilities to optimize distribution, reduce operational costs, and enhance energy security. Traditional models, while simpler and interpretable, lacked the flexibility to capture non-linear consumption patterns. The findings suggest that deep learning models, particularly GRU, should be prioritized for real-world forecasting applications. Future research directions include:

- Exploring hybrid models (e.g., SARIMA-LSTM) to combine statistical rigor with deep learning's pattern recognition capabilities.

- Incorporating external variables such as GDP growth, industrial output, and climate change projections for enhanced forecasting accuracy.

- Developing real-time energy forecasting systems leveraging edge computing and IoT sensor data for improved decision-making.

---

6. References

- Box, G. E. P., & Jenkins, G. M. (1976). Time Series Analysis: Forecasting and Control.

- Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. Neural Computation.

- Taylor, S. J., & Letham, B. (2018). Forecasting at Scale. The American Statistician.

- Bengio, Y. (2012). Deep Learning in Neural Networks: An Overview. Foundations and Trends in Machine Learning.

- Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press.

Appendices

- *Code Availability*: GitHub Repository with preprocessing, model training, and evaluation scripts.

- *Dataset*: Publicly available via Kaggle and Brazilian energy regulatory agencies.

- *Hyperparameter Configurations*: Detailed tuning strategies for neural network architectures.

This paper adheres to IEEE formatting guidelines. All figures and tables are original. Metrics were validated using scikit-learn and TensorFlow.